

# The persistence of social signatures in human communication

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The social brain hypothesis has suggested that social network size (and structure) is constrained by a combination of cognitive processes and the time required to service social relationships. We test this hypothesis in humans using a unique 18-month mobile phone dataset by examining changes in the structure of social networks across a major change in subjects' social and geographical circumstances. Our analysis reveals that the time allocation patterns of call frequency by participants to network members have a distinctive overall shape, where a small number of top-ranked network members received a disproportionately large fraction of calls, with some individual variation. However, importantly, whilst there was a large turnover of individual network members, these changes have little effect on the time allocation patterns of each individual: individuals thus displayed a distinctive "social signature" that was both persistent over time and independent of the identities of the network members. This provides the first direct evidence that social networks are constrained by a combination of cognitive constraints and the time individuals have available for social interaction, confirming one of the key assumptions of the social brain hypothesis.

Keywords: social brain hypothesis, time allocation, social networks, mobile phone

## I. INTRODUCTION

The social brain hypothesis [1, 2] suggests that there are general time and cognitive constraints on the number of relationships an individual can maintain at particular levels of emotional intensity [3, 4]. Close, emotionally intense relationships appear to play an especially important functional role in social species like primates: having strong and supportive relationships is essential for health and wellbeing [5, 6] and is known to have an impact on females' fitness [7, 8]. Since time is inelastic and, at least in humans, there is a direct relationship between the time devoted to a relationship and its emotional strength [9], this can be expected to result in a trade off between quantity and quality of relationships [4]. In addition, the social brain hypothesis [1, 6] and subsequent neuroimaging studies that have tested this [10–13] suggest that there is also a cognitive constraint on the number of relationships that an individual can maintain. These constraints result in a layered structure to personal networks, such that an individual can be envisaged as sitting in the centre of a series of concentric circles of acquaintanceship, with the relationships in these layers increasing in number but decreasing in emotional intensity [4, 6].

Although it has always been assumed that these layers are fixed in size, it has never formally been shown that individuals do not (or cannot) increase the number of close relationships (i.e. the number of individuals in any given network layer) when they form new relationships. Whilst there is often considerable instability in individual social relationships [14], it has in fact been suggested

that there is a greater level of stability at the level of personal networks – the set of ties an individual (ego) has to their family and friends (alters) [15, 16]. We use a unique 18 month longitudinal dataset on humans that combines detailed data on communication patterns from mobile phone records with questionnaire data to explore changes in the personal networks of individuals undergoing a major social transition: the move from school to university. We test the hypothesis that the number of close relationships and the time invested in them remain invariant even when there is significant turnover in network membership.

Our approach extends previous work in this area in three key ways. First, we have complete records of all calls an ego made to alters in their personal network over 18 months (including calls to landline numbers), rather than just a subset of calls an ego made to alters who happened to be on the same mobile network as them, as has usually been the case in previous work. Second, by combining information from the phone records with questionnaire data, we are able to uncover the structure of personal networks, in terms of how the nature of social relationships relates to calling patterns. Third, we are able to determine the proportion of an ego's personal network captured by the phone records, as well as the characteristics of the alters present in personal networks but not present in the phone records. We rank all alters of an ego based on the number of calls they receive, and are thus able to establish each ego's distribution of time (quantified by mobile phone calls) over alter ranks, an ego's "social signature". We then determine whether this social signature persists during a period of flux for social relationships with many alters both entering and leaving the network [9, 17, 18].

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## II. METHODS

### A. Personal network survey and call records

We used longitudinal data on the social networks of thirty participants (15 males and 15 females, aged 17 to 19 years old: mean $\pm$ SD age 18.1 $\pm$ 0.48) in their last year of secondary school, collected over an 18-month period during the transition from school to university (for full details, see Roberts & Dunbar [9]). Participants completed a questionnaire on their active personal network at three points in time: at the beginning of the study ( $t_1$ ), at 9 months ( $t_2$ ) and at 18 months ( $t_3$ ). The analysis in this study is based on the 24 participants (12 males, 12 females) who completed all three questionnaires and frequently used their mobile phones throughout the study. To elicit their personal network, participants were asked to list all unrelated individuals "for whom you have contact details and with whom you consider that you have some kind of personal relationship (friend, acquaintance, someone you might interact with on a regular basis at school, work or university)". The participants were also asked to list all their known relatives. For all individuals listed, participants were asked to provide both landline and mobile phone numbers. In each survey ( $t_1$ ,  $t_2$ ,  $t_3$ ), for both kin and friends/acquaintances, the participants were asked to indicate the emotional intensity of the relationship by providing an emotional closeness score, measured on a 1–10 scale, where 10 is someone "with whom you have a deeply personal relationship".

At  $t_1$ , all participants lived in the same large UK city ("City A"). At month 4 of the study, the participants took their final exams at school ("A-levels") and left the school. Of the 24 participants who completed all three questionnaires, six participants stayed in City A and worked, not going to University; eight went to university in City A (which has two large universities) and the remaining 10 went to university elsewhere in England.

In compensation for participating in the study, participants were given a mobile phone, with an 18-month contract from a major UK mobile telephone operator. The line rental for the mobile phone was paid for, and included 500 free monthly voice minutes (to landlines or mobiles) and unlimited free text messages. For each participant, we obtained itemized, electronic monthly phone invoices that listed all outgoing calls (recipient phone number, time and duration of calls). The electronic PDF invoices were parsed into machine-readable form. The questionnaire data and the call dataset form the main basis for our analysis.

### B. Constructing ego-centric call networks

For each participant in the study (ego), we used the list of kin and friends/acquaintances (alters) generated in response to the three social network questionnaires and

combined it with the electronic phone invoices to construct a set of ego-centric call networks. If an alter was listed as having multiple phone numbers, a mobile and a fixed line number, a call by the ego to either number was recorded as a call between ego and alter. Phone numbers appearing on the invoices but not listed in the questionnaire responses were treated as unique alters; however, service numbers (such as those with 0800 prefixes) were filtered out. The 18-month observation period of electronic phone invoices was divided into three consecutive intervals of 6 months each ( $I_1$ : March-August,  $I_2$ : September-February,  $I_3$ : March-August). For each ego in each of the three intervals, we counted the total number of his/her outgoing calls and the number of calls made to each alter. Comparing the ego-alter relationships, as reported by the egos via emotional closeness scores from the survey data, with the egos' real calling behaviour, we determined the fraction of self-reported ego relationships appearing in the calling records. Using the alter-call-counts per interval, we ranked the egos from most called to least called, calculated a time allocation pattern (Zipf plot) depicting the total fraction of calls to an alter as a function of the alter's rank, and calculated average emotional closeness as a function of alter's rank for all 24 egos.

### C. Comparison of ego-reported relationships to phone call records

In most previous studies of human communication using auto-recorded data [3, 19–25] an alter appears in the data only if there is communication between the ego and alter. Thus, if communication occurs between ego and alter via a channel not being studied (e.g. landline calls, calls on other mobile networks to the one under investigation) the alter is never known. Here we use the list of alters, kin and friends/acquaintances, from the survey data and the ego-reported emotional closeness score for these alters to understand the characteristics of those alters missing from the data call pattern analysis.

Let us consider the calling behaviour of each ego towards its alters of varying emotional closeness. Let  $A(g, c_{t_i}, I_i)$  be the set of alters of ego  $g$  called in time interval  $I_i$  that were categorized in the survey at time  $t_i$  with emotional closeness  $c_{t_i}$ . Similarly, let  $L(g, c_{t_i}, I_i)$  be the set of alters of specified emotional closeness  $c_{t_i}$  during time interval  $I_i$  that were callable by ego  $g$ . An alter was callable during time interval  $I_i$  if the alter was first listed in the survey data at  $t_j$  or was in the set  $A(g, \circ, I_j)$  where  $i \geq j$ . The fraction of alters called by  $g$  with emotional closeness  $c_{t_i}$  in time interval  $I_i$  is simply,

$$f(g, c_{t_i}, I_i) = \frac{|A(g, c_{t_i}, I_i)|}{|L(g, c_{t_i}, I_i)|}, \quad (1)$$

where numerator and denominator give the cardinality for each set.

### D. Analyzing time allocation patterns

We quantify the variation between the sets of alters an ego calls in two time intervals with the Jaccard coefficient,

$$J(I_i, I_j) = \frac{|A(I_i) \cap A(I_j)|}{|A(I_i) \cup A(I_j)|} \quad (2)$$

where  $A(I_i)$  and  $A(I_j)$  are the sets of alters called by the ego in two time intervals  $I_i$  and  $I_j$ , respectively. Then  $J = 1$  if the sets are the same, and  $J = 0$  if the sets have no common alters. For a pairwise comparison of the time allocation patterns between two different egos or two different time intervals for a single ego we measure the Jensen-Shannon divergence (JSD) [26] defined as

$$JSD(P_1, P_2) = H\left(\frac{1}{2}P_1 + \frac{1}{2}P_2\right) - \frac{1}{2}[H(P_1) + H(P_2)], \quad (3)$$

where  $P_1$  and  $P_2$  are the two time allocation patterns where  $P_i = \{p_i(r)\}$  such that  $p_i(r)$  is the fraction of calls to the alter of rank  $r$  in pattern  $i$ . Additionally,  $H(P)$  is the Shannon entropy,

$$H(P) = -\sum_{r=1}^k p(r) \log p(r), \quad (4)$$

where  $p(r)$  is as above and  $k$  is the maximum rank, *i.e.* the total number of alters called. The Jensen-Shannon divergence is a generalized form of the Kullback-Leibler divergence (KLD) such that  $JSD(P_1, P_2) \in [0, \infty)$ , and  $JSD(P_1, P_2) = 0$  iff the distributions are identical. We chose JSD over KLD due to its capacity to deal with zero probabilities  $p(r) = 0$ . The maximum number of alters called by an ego in a given time interval,  $k$ , varies depending on the ego and the interval; therefore, if  $k_2 > k_1$  is the larger number, we assign  $p_1(r_1) = 0$  for  $k_1 > r_1 \geq k_2$ , *i.e.* zero-pad the series of fractions of calls such that they are of the same length. Additionally, for validating the pairwise comparison results, we also calculated the  $\ell^2$ -norm for pairs of time allocation patterns, defined as  $\ell^2 = \sqrt{\sum_{r=1}^k |p_1(r) - p_2(r)|^2}$ .

## III. RESULTS

### A. Strength of ego-identified relationships and real calling behaviour

The calls egos place to their alters are related to the strength of the ego-alter relationship, as measured by the ego-reported emotional closeness score. In plotting the average number of alters an ego will call in a 6-month time interval,  $I_i$ , as a function of the emotional closeness score,  $c_{t_i}$ , we see a positive relationship between fraction of alters called and the average alter emotional closeness

score (Fig. 1, main panel). The small sample size does result in large values for standard deviation, as shown by the shaded regions. Furthermore, we see that on average an ego will place at least one call within a given 6-month time interval to four out of five alters that the ego scored with emotional closeness 8 or higher. Thus, the alters rated as most emotionally close to the ego are likely to appear as the most frequent contacts in auto-record phone data. We see that the phone data do not document every close ego-alter relationship; to fully capture an ego's interaction with all of its alters we would need to collect data on phone calls, emails, Facebook communications, face-to-face interactions, etc., which would be a daunting undertaking. Nonetheless, several studies have demonstrated that frequency of contact is a reliable index of emotional closeness in relationships [27, 28], and these datasets confirm that frequency of contact by telephone and other digital media (text, email) correlates significantly with frequency of face-to-face contact ( $p \ll 0.0001$  in each case,  $N=1006$  and  $N=8967$ , respectively).

Moving beyond the binary accounting of whether or not an ego calls an alter given a particular emotional closeness and time interval, we calculate the average emotional closeness scores of alters by their ranked call frequency. The inset plot in Fig. 1 shows the average emotional closeness, and standard deviation via error bars, of the top 40 most called alters for all egos over all three time intervals. In the inset plot, we see that average emotional closeness decreases with increasing alter rank. It is not that alters with low emotional closeness scores are excluded from the top ranks of the most called alters, but on average the most called alters do have higher emotional closeness scores than those alters called less frequently.

### B. Time allocation patterns and their persistence

For almost all individuals in the survey, the time allocation patterns are characterized by a heavy tail that decreases slower than exponentially. A large fraction of communication is typically allocated to a small number of top-ranked alters: for male (female) participants, the fraction of calls to the top alter is on average  $0.20 \pm 0.09$  ( $0.26 \pm 0.08$ ), and the fraction of calls to the top three alters is  $0.41 \pm 0.12$  ( $0.50 \pm 0.11$ ). A similar tendency to communicate electronically mostly with only a few others has been observed earlier for text messages [29, 30] and Facebook [31]. This shape of the time allocation pattern is in line with the layered network view, where the innermost layer contains a small number of alters with close emotional ties that require large maintenance effort. It should be noted that the call activity level of each participant varies a lot in time; on average, the participants made  $1030 \pm 691$  calls per 6-month interval. For some individuals, the difference between the maximum and minimum 6-month call counts was  $> 600$  calls.

Figure 2 shows the time allocation patterns for two specific egos for each of the three time intervals (a male

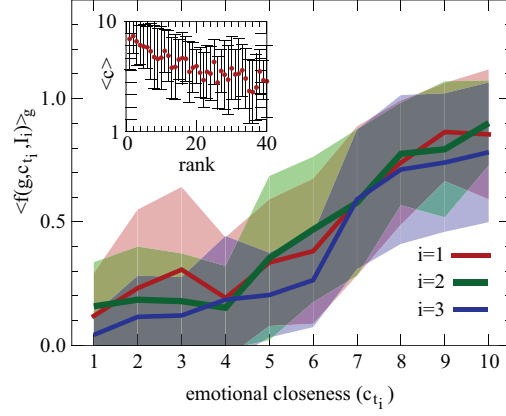


FIG. 1: Relationship between call pattern and emotional closeness scores attributed to alters. The main figure illustrates the fraction of alters, averaged over all egos,  $\langle f(g, c_{t_i}, I_i) \rangle_g$ , that are actually called by an ego in a 6-month period,  $I_i$ , given that the ego scores the alter with emotional closeness  $c_{t_i}$  in the survey at time  $t_i$ . The shaded region indicates the standard deviation. The inset shows the average emotional closeness of alters of varying rank with error bars showing the standard deviation.

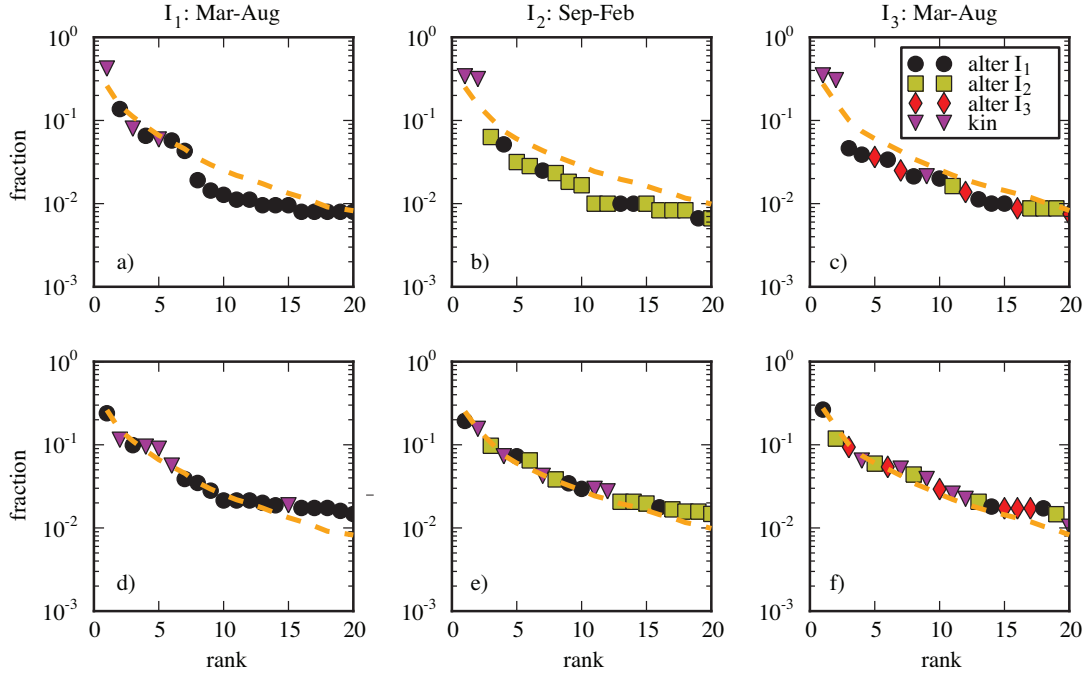


FIG. 2: Time allocation patterns for two different egos (survey participants) (top and bottom rows), displaying the fraction of calls to each alter called as a function of alter rank, for the three 6-month time intervals (columns). The symbols correspond to alters observed for the first time in intervals  $I_1$  (circles),  $I_2$  (squares), and  $I_3$  (diamonds), or to kin (triangles) as reported by the egos. The dashed line indicates the time allocation pattern averaged over all 24 egos.

whose pattern deviates from the average, and a female with a pattern close to average), together with the pattern averaged over all 24 egos. The ego whose patterns are depicted in the upper row (panels a to c) is a male who went to university in another city, and the lower row (panels d to f) represents a female who went to university in City A. For the upper row, the top-ranking alters receive a very large fraction of calls and persistently in-

clude two family members (triangles), whereas for the networks in the lower row, the top alters are less dominant, kin are ranked lower, and kin display larger rank fluctuations.

It is also clear on the basis of Figure 2 that the alter composition of the networks undergoes major changes. For both egos shown here, the networks corresponding to the second 6-month interval ( $I_2$ ) are dominated by

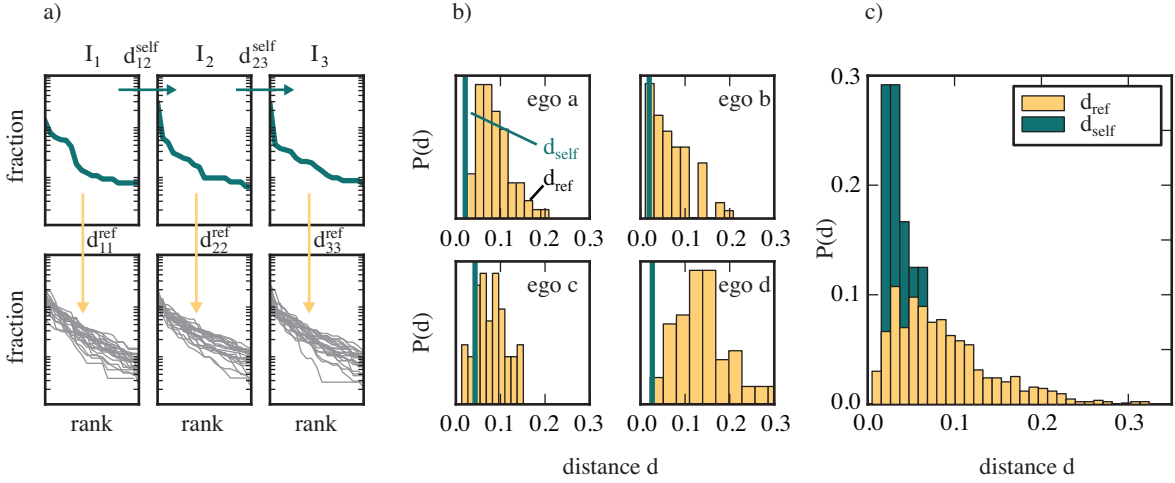


FIG. 3: Persistence of time allocation patterns. a) A schematic of how the distances based on Jensen-Shannon divergences are calculated. For the focal ego (top row), self-distances ( $d_{self}$ ) are calculated for patterns in consecutive intervals and averaged. Reference distances ( $d_{ref}$ ) are calculated for each interval between the patterns of the focal ego and all other egos (bottom row). These are averaged over the three intervals for each pair of egos (focal, other). b) Values of the average self-distances ( $d_{self}$ ) and histograms for reference distances ( $d_{ref}$ ) for four example egos. c) Distributions of self-distances and reference distances, for all egos.

newcomers, *i.e.* alters that were first observed in  $I_2$ . This reflects the period of change that the egos are going through:  $I_2$  represents the first six months of the first academic year for those participants who went to university. Overall, as quantified by the Jaccard coefficient, the similarities between the sets of alters in consecutive intervals, averaged over all respondents, are  $J(I_1, I_2) = 0.20 \pm 0.08$  and  $J(I_2, I_3) = 0.26 \pm 0.09$  for the full set of alters. Thus there is more turnover between intervals  $I_1$  and  $I_2$  (two-sample unequal variance  $t$ -test:  $t = 2.126$ ,  $p = 0.039$ ). However, if we only consider top 20 ranking alters, the similarities are higher:  $J(I_1, I_2) = 0.34 \pm 0.12$  and  $J(I_2, I_3) = 0.44 \pm 0.10$  (the means are different with  $t = 2.961$ ,  $p = 0.005$ ). Nonetheless, it is clear that the variation is not solely due to high turnover in the lowest ranks.

In order to measure the changes in the time allocation patterns over time, we apply the Jensen-Shannon divergence as a measure of the distance between patterns. In order to quantify how similar an individual's patterns for consecutive windows are, we calculated i) the distances between one ego's pattern for consecutive windows, and ii) the averaged distances between the patterns for the focal ego and all other egos within an interval (see Fig. 3 a). We then calculated self and reference distances  $d_{self}$  and  $d_{ref}$  such that  $d_{self}$  was averaged over the two distances between consecutive windows,  $d_{self}^i = \frac{1}{2}(d_{12}^i + d_{23}^i)$ , where  $i$  indicates the focal ego and sub-indices denote time intervals. Reference distances were averaged for each pair of egos over the three time windows,  $d_{ref}^{ij} = \frac{1}{3}(d_{11}^{ij} + d_{22}^{ij} + d_{33}^{ij})$ , where  $j$  denotes non-focal egos.

The results in Figure 3 (panels b and c) clearly indicate that on average, the shapes of the time allocation patterns of participants (the social signatures) show a tendency to persist in time, as the distance values  $d_{self}$  between one participant's consecutive patterns are on average much lower than the distances  $d_{ref}$  to other participants. On average, for each ego,  $80\% \pm 13\%$  of the distances to others were greater than  $d_{self}$ . Averaged over all egos, the average self-distance was  $\langle d_{self} \rangle = 0.037 \pm 0.015$  while the average distance to other egos was  $\langle d_{ref} \rangle = 0.087 \pm 0.044$  ( $\langle d_{self} \rangle < \langle d_{ref} \rangle$  with  $t = 13.3$ ,  $p \ll 10^{-6}$ , two-sample unequal variance  $t$ -test). Using the  $\ell^2$ -norm as an alternative distance measure yields a qualitatively similar outcome ( $\langle d_{self} \rangle = 0.10 \pm 0.04$ ,  $\langle d_{ref} \rangle = 0.16 \pm 0.09$ ,  $\langle d_{self} \rangle < \langle d_{ref} \rangle$  with  $t = 6.04$ ,  $p < 10^{-6}$ ).

#### IV. DISCUSSION

In this study, we used a unique longitudinal dataset, combining detailed mobile phone call records with three waves of survey data, to examine the personal networks of participants during a period of natural flux in their social relationships. Our key findings can be summarized as follows: (1) There is a clear relationship between the emotional intensity of alters and the frequency of calls made to them. (2) The frequency of calls to alters is broadly similar across all individuals, with a small number of top-ranked alters receiving a disproportionately large fraction of calls. However, we also observe considerable heterogeneity in the detailed pattern of how different individuals allocate time to their alters. (3) Although network

compositions undergo major changes, with many alters entering and leaving a network and relationships increasing and decreasing in intensity, these changes are seen to have surprisingly small effects on the time allocation patterns. Thus, individuals appear to have a "social signature" in that they allocate roughly the same amount of time to their alters depending on their rank, independent of who these alters are. Such signature patterns show variation between participants but appear persistent over time for each participant. This provides the first direct evidence for the claim [1, 4] that social networks are constrained in some way either by cognition or by the time individuals have available for social interaction, or both: when new relationships are acquired, old ones are inevitably downgraded. As such, this confirms one key assumption underpinning the social brain hypothesis that is thought to be responsible for the layering of social networks.

When reflected against the prediction of a layered structure of personal networks from the social brain hypothesis, our observations can broadly speaking be considered in accordance with the main characteristics where the networks comprise a small number of relationships of high emotional intensity, with increasing numbers of relationships of lower emotional intensity. Discrete layer boundaries where the communication frequency drops abruptly were observed for some egos (see Fig. 2, top row) within some of the time intervals; however, there

was a lot of individual variation. This is to be expected: while emotional intensity was seen to correlate with call frequency, calls are only one of the possible communication modalities, and social interactions carried out, e.g., by face-to-face contacts were not included in our analysis.

More broadly, our approach shows the value of combining subjective survey data, (e.g. on the emotional intensity of relationships) with the digital traces of electronically-mediated communication. Both of these sources of data have their limitations, but by combining the two, important insights can be gained about how the objective pattern of communication relates to the nature of our social relationships (e.g. [32]). Future work could use this combined data to further our understanding of how patterns of communication relate to specific types of social tie. For example, if there are clear differences in the patterns of mobile communication between family members, and communication between friends, it might be possible to use these to infer social relationships, based solely on communication patterns, from mobile datasets where information on the nature of the social interactions is lacking.

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